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### **New Evidence on the Determinants of Absenteeism Using Linked Employer-Employee Data**

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**Abstract:**

In this paper, we provide new evidence on the determinants of absenteeism using the Workplace Employee Survey (WES) 1999-2002 from Statistics Canada. Our paper extends the typical labour-leisure model used to analyze the decision to skip work to include firm-level policy variables relevant to the absenteeism decision and uncertainty about the cost of absenteeism. It also provides a non-linear econometric model that explicitly takes into account the count nature of absenteeism data and unobserved heterogeneity at both the individual and firm level. Controlling for very detailed demographic, job and firm characteristics (including workplace practices), we find that dissatisfaction with contracted hours is a significant determinant of absence.

**Keywords:** Absenteeism, Linked Employer-Employee Data, Unobserved Heterogeneity, Count Data Models

**JEL Classification:** J22, J29, C23

# 1 Introduction

In this paper, we provide new evidence on the determinants of absenteeism using linked employer-employee data. It has long been recognized that while the decision to skip work is made by the individual, reasons for doing so might also be related to personnel considerations or the organizational structure of the firm (Frankel (1921)). Linked data thus provides a unique opportunity to disentangle conflicting causes of absenteeism.

Despite its rising frequency and associated cost, there are relatively few studies on the determinants of absenteeism. Moreover, it could be argued that most of the existing studies on the determinants of absenteeism suffer from the use of less than adequate data. A first strand of the literature focuses on only one kind of absenteeism, namely absenteeism due (officially) to health reasons. These studies generally use data from a health insurance company or government agency.<sup>1</sup> A second strand of the literature uses detailed absenteeism data from one company or a very small sample of firms<sup>2</sup>. It is not clear that their results are generalizable outside their small samples.<sup>3, 4, 5</sup>

Our work is thus more closely related to the second strand of the literature

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<sup>1</sup>For example, Henrekson and Persson (2004) use aggregate data from the National Social Insurance Board of Sweden, Johansson and Palme (2002) use data from the 1991 Swedish Level of Living Survey (SLLS). In the U.S., Vistnes (1997) uses the 1987 National Medical Expenditure Survey.

<sup>2</sup>Kauermann and Ortlieb (2004) have absenteeism data from one German firm. Barmby (2002) also has data on only one UK manufacturing firm. Delgado and Kiesner (1997) focus on London buses operators. Drago and Wooden (1992) work on a sample of 15 firms from the U.S., Canada and New-Zealand. Barmby, Orme, and Treble (1991) use data on four factories of an unidentified firm. Wilson and Peel (1991) have data on a sample of 52 firms in the engineering and metal industry in the United Kingdom. Dunn and Youngblood (1986) use 1977 data from one utility company.

<sup>3</sup>A notable exception is Allen (1981) who uses the 1972-73 Quality of Employment Survey. However, this survey does not have any information about the employer and therefore cannot be used to study the link between workplace practices and absenteeism.

<sup>4</sup>Other papers focusing on absenteeism include Gilleskie (1998) who focuses on the absenteeism decision of individuals with acute illnesses, Ehrenberg (1970) who studies the link between absenteeism and the decision of the firm to use overtime, and Allen (1983) who estimates the cost of absenteeism.

<sup>5</sup>A third strand takes a more macroeconomic approach. For example, Kenyon and Dawkins (1989) use aggregate Australian time-series data.

using employee level data. However, we examine the determinants of absenteeism using survey data, the Workplace Employee Survey (WES) 1999-2002 from Statistics Canada. The use of WES has numerous advantages for the study of the determinants of absenteeism: (1) the survey is designed to be representative of the whole universe of firm operating in Canada; (2) in each sampled firm, a subset of workers from the firm was sampled so that the survey is also representative of the universe of workers in Canada<sup>6</sup>; (3) since the survey is linked, we have detailed micro data on each of these workers, including days of absenteeism during the year, demographic and job characteristics, preferences and human capital variables (this is in addition to the usual firm-level characteristics); (4) each worker was asked to recall the number of days absent from work in the past year; (5) the linked nature of the data allows us to take into account firm unobserved heterogeneity; (6) and the longitudinal nature of the data allows us to take into account worker unobserved heterogeneity.

We start first by extending the typical labor-leisure model used to analyze the decision to skip work to include firm-level policy variables relevant to the absenteeism decision and uncertainty about the cost of absenteeism to the worker. We next describe an econometric model that explicitly takes into account the count data nature of absenteeism data and also incorporates unobserved heterogeneity at both the individual and firm level. Data sources and variable descriptions are presented in Section 4. We describe the results in section 5 and briefly conclude in the final section.

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<sup>6</sup>Abowd and Kramarz (1999) classify WES as a survey in which both the sample of workplaces and the sample of workers are cross-sectionally representative of the target population.

## 2 Theoretical Framework

We use the typical labor-leisure choice model to study the absenteeism decision (see Allen (1981), Allen (1983), Barmby, Orme, and Treble (1991), Delgado and Kiesner (1997) and Dunn and Youngblood (1986))<sup>7</sup>. We assume that each job offers a work schedule as well as a wage rate. Since search is costly, a worker may accept a job offer even though at the contracted number of work hours ( $t^c$ ) his marginal rate of substitution between leisure and income does not equal the wage rate ( $w$ ). When a worker contracts for more than his desired hours given  $w$ , he retains an incentive to consume more leisure. One way of doing so is to be absent from work. In this theoretical framework, an emphasis will be placed on the explicit random cost of such a decision and on how the firms and jobs characteristics affect this decision. These two aspects will become important in the empirical part of the paper and have not been addressed in the literature.

Absenteeism results in lost output when the absent worker is replaced by someone who is generally less efficient or is not replaced at all. For the employment relation to continue, the firm must be compensated for this loss. In addition to losing earnings he would have received if he had reported, the worker faces a penalty ( $D$ ) for each scheduled work period missed. In practice, this penalty will be observed in the form of a decreased probability of receiving a promotion or merit wage increase and an increased likelihood of being dismissed. Denoting time absent from work as  $t^a$ , one can then write

$$D = D(t^a) \quad D' \geq 0, \quad D'' \geq 0, \quad D(0) = 0$$

The workers who miss the most days pay the largest penalties. The costs of increased amounts of absenteeism to the firm are presumed to be non-decreasing,

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<sup>7</sup>The following discussion is also drawn from Vistnes (1997) and Johansson and Palme (1996). See Hausman (1980) and Blomquist (1983) for the foundations of the basic model.

yielding a constant or graduated penalty structure. Workers with perfect attendance records are not penalized at all. Since the worker does not really know this potential cost when he makes his decision, we consider the possibility that  $D(t^a)$  can be a random variable. So, we write  $\tilde{D}(t^a)$  when this is the case.

Holding work schedule flexibility constant, the work attendance decision can be analyzed within the traditional labor-leisure choice framework. Workers maximize an expected utility function containing consumption ( $C$ ) and leisure time ( $L$ ) as its arguments<sup>8</sup>

$$EU = EU(C, L; P, F). \quad (1)$$

The expected utility of the worker is also a function of a vector of personal characteristics ( $P$ ) and a vector of firm characteristics ( $F$ ). Letting  $R$  equal the individual non-labor income, the budget constraint of the worker is

$$R + w(t^c - (1 - s_L)t^a) - \tilde{D}(t^a) = C \quad (2)$$

where the price of the consumption good  $C$  is normalized to one and  $s_L$  is a variable that takes the value of one if a worker has full sick leave benefits<sup>9</sup> and less than one otherwise. Workers also face a time constraint of

$$t - t^c - t^a - t^l = 0 \quad (3)$$

where  $t$  represents the total amount of time in the period under consideration and  $t^l$  is leisure hours. So we can write  $t^a + t^l = L$ . Substitution of (2) and (3)

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<sup>8</sup>See Dionne and Eeckhoudt (1987) for such a theoretical framework.

<sup>9</sup>We use the same hypothesis as Vistnes (1997) of modelling  $s_L$  as a binary variable due to data limitations. As in Vistnes (1997), detailed information on sick leave provisions, such as the stock of sick leave, carry-over provisions, whether sick leave benefits pay the worker fully or partially, and whether the sick leave can be applied toward early retirement or used for maternity leave, is not available. Detailed job characteristics in the empirical analysis may serve as proxies for these provisions.

in (1) and differentiation of the latter with respect to  $t^a$  produces the first-order condition

$$E \left[ U_L - (w(1 - s_L) + \tilde{D}'(t^a))U_C \right] = 0 \quad (4)$$

where  $U_k > 0$  indicates the partial derivative of  $U$  with respect to  $k = L, C$ . The variable  $\tilde{D}(t^a)$  can be expressed more directly by defining  $w^a$  as the cost of being absent. So we can write  $\tilde{D}(t^a) = w^a t^a$  and, as already mentioned,  $w^a$  can be a random variable when the decision on  $t^a$  is made. In this case, the first order condition (4) becomes

$$E [U_L - (w(1 - s_L) + w^a) U_C] = 0. \quad (5)$$

A worker will be absent on any given day as long as the extra leisure is more valuable to him than the sum of the wages he would have earned that day and the resulting loss in future earnings. This means that the shadow price of time for absent workers is greater than the contracted wage.

By differentiating the first-order conditions for  $s_L = 0$  and applying Cramer's Rule, one can show, under the usual conditions of an upward sloping labor supply curve, that

$$\frac{\partial t^a}{\partial w} < 0, \quad \frac{\partial t^a}{\partial R} > 0, \quad \frac{\partial t^a}{\partial t^c} > 0, \quad \frac{\partial t^a}{\partial Risk} < 0, \quad \frac{\partial t^a}{E(w^a)} < 0. \quad (6)$$

where Risk is a measure of the risk associated to  $w^a$  and  $E(w^a)$  its mean. See Dionne and Eeckhoudt (1987) for a sufficient condition yielding  $dt^a/dRisk < 0$ . (Details for the derivation of results in (6) are in Appendix).

The effect of a change in the wage rate on time absent from work is ambiguous a priori because income and substitution effects operate in opposite directions. However, under the conditions of an upward sloping labor supply curve, a negative sign is obtained when  $s_L = 0$  or is sufficiently small. An in-

crease in non-labor income leads to more demand for all non-inferior goods and services, including time absent from work. If the number of contracted hours changes, the number of absences move in the same direction. Increased penalties for absenteeism reduce the number of days missed; as does an increased risk of penalty.

In cases where full sick leave is available, the product of  $w$  and  $t^a$  disappears from (2) and the first-order equilibrium condition becomes

$$E[U_L - w^a U_C] = 0. \quad (7)$$

Unless the penalty function is made steeper, an individual will be absent more frequently in plants where sick leave is fully paid to absent workers. It should be noted that the effect of a wage change on the likelihood of absence is unambiguously positive in this case because there is no longer a substitution effect.

Denoting the scheduling flexibility permitted by one's employer as  $f$  (we expect  $\partial t^A / \partial f < 0$ ), the model can be summarized as

$$t^A = t^A( \quad w, \quad R, \quad t^c, \quad E(w^a), \quad Risk, \quad f ). \quad (8)$$

(−)   (+)   (+)   (−)   (−)   (−)

We provide a structural form for these relationships in the next section.

### 3 Empirical Specification

From the above behavioral model, we can derive a structural econometric model of the absenteeism decision. Extending the model of Hausman (1980) and Blomquist (1983) proposed for labor force participation, we can write the fol-



lowing functional form for the utility function:

$$U(C, t^a + t^l; P, F) = \exp \left\{ - \left( 1 + \frac{\beta (C + \bar{P} + \bar{F})}{b - t + (t^a + t^l)} \right) \right\} \left( \frac{t - (t^a + t^l) - b}{\beta} \right) \quad (9)$$

where

$$\bar{P} = P/\beta - \alpha/\beta^2, \bar{F} = F/\beta - \alpha/\beta^2, \quad b = \alpha/\beta,$$

$\alpha$  and  $\beta$  are parameters and absolute risk aversion is assumed equal to one<sup>10</sup>.

From this utility function, one can verify that the first order condition yields

$$t^a = t^c - \alpha (w(1 - s_L) + E(w^a) + 1/2\sigma^2) - \beta(R + t^c w s_L) - \gamma P - \eta F \quad (10)$$

assuming normal distribution for  $w^a$ , which yields  $\sigma^2$  as the measure of risk. In a more compact form, (10) can be rewritten as

$$t^a = t^c - \alpha w^* - \beta R^* - \gamma P - \eta F$$

where  $w^*$  can be interpreted as the relative cost of being absent and  $R^*$  as the virtual benefit or income related to absence. A positive  $\alpha$  parameter and a negative  $\beta$  parameter are expected.

In this simple model, when preferences are not random, days of absenteeism can be represented by a Poisson process (see Hausman, Hall, and Griliches (1984); Gouriéroux, Monfort, and Trognon (1984)). In fact, since absences are recorded as non-negative integers, modeling such data with a continuous distribution could lead to inconsistent parameter estimates. Let  $t_{ijt}^a$  be the observed number of days of absenteeism for employee  $i$  in firm  $j$  at time  $t$ . The

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<sup>10</sup>See Johansson and Palme (1996), for a similar model where the firms variables are not considered and  $w^a$  is not present in the budget constraint.

basic model is

$$P(t_{ijt}^a \mid \lambda_{ijt}) = \frac{e^{-\lambda_{ijt}} (\lambda_{ijt})^{t_{ijt}^a}}{t_{ijt}^a!} \quad (11)$$

with

$$\lambda_{ijt} = t_{ijt}^c - \alpha w_{ijt}^* - \beta R_{ijt}^* - \gamma P_{it} - \eta F_{jt} > 0.$$

It should be repeated that  $t_{ijt}^c$  (contracted hours) are exogenous in the model. This decision variable is already fixed when the worker (or nature) makes a decision about  $t^a$ .

It is typical to introduce unobserved heterogeneity in the Poisson model in a multiplicative form through  $\lambda_{ijt}$ . Unobserved heterogeneity should be present because many non observable factors in the data set can affect the sensitivity to economic incentives related to work absence decisions. We use the following parameterization for  $\lambda_{ijt}$

$$\lambda_{ijt} = \exp(\delta_{ij} + \psi_j + \theta_{ij}) \quad (12)$$

where

$$\delta_{ij} = t_{ijt}^c - \alpha w_{ijt}^* - \beta R_{ijt}^* - \gamma P_{it} - \eta F_{jt}$$

The additional parameter  $\psi_j$  captures unobservable factors of the firm orthogonal to other observed firm characteristics. We assume firm unobserved heterogeneity to be normally distributed with mean zero. The variance of  $\psi_j$  ( $\sigma_\psi$ ) is identified by the observation of many workers coming from the same firm.

Since we do not observe worker mobility due to the design of the survey, we do not include pure worker unobserved heterogeneity but because of the longitudinal nature of the data, we have repeated observations on the employer-employee relationship which allows us to take into account unobserved job heterogeneity ( $\theta_{ij}$ ). We also assume that  $\theta_{ij}$  is distributed normally with variance

$\sigma_\theta$  and is orthogonal to  $\psi_j$ <sup>11</sup>. Firm unobserved heterogeneity might proxy for the cost of absence to the firm when observed heterogeneity is not sufficiently informative. For example, the cost of absence to the firm might be pretty low if substitute workers are easily available and are as productive as regular workers (Allen (1983)) and therefore, the econometrician might observe higher absenteeism than in an otherwise identical firm where such substitute workers are not available. From a statistical point of view, it is necessary to take into account both sources of heterogeneity in order to avoid the problem of spurious regressions due to multiple observations on the same worker over time and the same firm characteristics over its employees.

The joint likelihood is obtained by numerically integrating out the heterogeneity components from the product of the conditional likelihoods of the firms, assuming joint normality of the heterogeneity components. Since a closed form solution to the integral does not exist, the likelihood was computed by approximating the normal integral by a weighted sum over “conditional likelihoods”, i.e. likelihoods conditional on certain well-chosen values of the residual.

## 4 Data

We use data from the Workplace and Employee Survey (WES) 1999-2002 conducted by Statistics Canada. The survey is both longitudinal and linked in that it documents the characteristics of the workers and of the workplaces over time. The target population for the “workplace” component of the survey is defined as the collection of all Canadian establishments who paid employees in March of the year of the survey. The survey, however, does not cover the Yukon, the Northwest territories and Nunavut. Establishments operating in fisheries, agri-

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<sup>11</sup>Note that this specification is not subject to the usual objections to the Poisson model since the inclusion of firm and worker unobserved heterogeneity allows for dispersion at both the worker and firm level.

culture and cattle farming are also excluded. For the “employee” component, the target population is the collection of all employees working, or on paid leave, in the workplace target population.

The sample for the workplaces comes from the “Business registry” of Statistics Canada which contains information on every business operating in Canada. Employees are then sampled from an employees list provided by the selected workplaces. For every workplace, a maximum of twelve employees are selected, and for establishments with less than four employees, all employees are sampled. In the case of total non-response, respondents are withdrawn entirely from the survey and sampling weights are recalculated in order to preserve representativeness of the sample. WES selects new employees and workplaces in odd years (at every third year for employees and at every fifth year for workplaces). We used the final sampling weights for employees as recommended by Statistics Canada in all our regressions.

We finally exclude establishments with less than ten employees from the sample because survey questions on work practices were not intended for them. Individuals who did no work throughout the year are also included but we control for their limited exposure to the risk of being absent in our regression framework. The rich structure of the data set allows us to control for a variety of factors determining absenteeism decisions. From the worker questionnaire, we are able to extract detailed demographic characteristics including measures of health, human capital, job satisfaction and income from other sources. Moreover, we use detailed explanatory variables on the employment contract including wage, contracted hours and information about working hours flexibility and when these working hours take place.

From the firm questionnaire, we are able to construct firm size indicators and build measures of turnover and vacancy rates. Even more important, the

establishment questionnaire includes very detailed information about changes in organizational practices (15 indicators) and current workplace practices (6). We complement those by adding some indicators for the type of nonwage benefits that the firm offers to its workers. Finally, our regressions include industry (13), occupation (6) and time (4) dummies. Summary statistics on all explanatory variables are presented in Table 1 for the dependent variable, Table 2 for the employees and Table 3 for the employer. Note that week absent in Table 1 refers to a five day workweek. Thus zero means the worker was absent strictly less than five days.

## 5 Results

Complete estimation results are presented in the multiple parts of Table 4. The first column presents results from the estimation of the standard Poisson model from equation (12) and column “IRR” shows the corresponding incidence rate ratios. The two next columns show estimation results from a zero-inflated Poisson (ZIP) model. This other model accounts for the prevalence of zero counts in the absenteeism data. The ZIP Poisson model also takes into account the fact that the determinants of zero counts could be different from the determinants of the number of days of absenteeism, due to job design or matching in the job market for example.

In all models, the dependent variable is the number of days of absence that are reported for the whole year. Note that the survey distinguishes between paid sick leave, unpaid leave and other paid leave<sup>12</sup>. Using days of absence in this type of survey might be problematic if the distribution of days of absence is not smooth. Moreover, it is possible that the respondent’s ability to recall absences

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<sup>12</sup>Other paid leave does not include vacations, paternity/maternity leave or absence due to strikes or lock-out.

for a full year is not as good as we would like it to be<sup>13</sup>. For these reasons, in our empirical analysis, we also tested the model using weeks of absenteeism as the dependent variable. Since results did not differ, we show only results for days of absenteeism<sup>14</sup>.

Note that we were not able to estimate the full specification with parametrization (12) since the firm and employee random effects are not nested. Non-linear models with more than one variance component are very hard to estimate due to their high dimensionality, especially if the random effects are not nested, which is the case with firm and individual heterogeneity. Many methods have been proposed to overcome such numerical difficulties (see Lee and Nelder (1996) and Jiang (1998)) but unfortunately, it turns out that none are robust enough to deal with data sets of the size we use in this analysis. We compared results between two specifications, workplace or worker unobserved heterogeneity and since results did not differ much between the two specifications, we present results including worker heterogeneity only. Finally, in what follows, we focus mainly on coefficients and incidence rate ratios from the Poisson model but discuss results from the ZIP model when they differ.

**Demographics and health** We find that women are likely more likely to be absent. Women have 1.17 times the absence rate of men and this effect is even stronger if there are kids younger than six years old in the household<sup>15</sup>. Being married reduces absenteeism but the effect is significant at the 10% level only. Health is also found to be a very important determinant of the absenteeism decision. Individuals with no activity limitation have less than half the incidence rate of individuals with activity limitations. The impact of health

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<sup>13</sup>Unfortunately, it is not possible to compare the number of absences as reported by the worker to administrative measures.

<sup>14</sup>The structure of the data also does not allow us to study episodes of absenteeism.

<sup>15</sup>Vistnes (1997) also finds a significant interaction between being a women and having young kids.

is slightly less important in the ZIP model but also a statistically significant positive determinant of the probability of having no absenteeism which suggests that individuals with activity limitations will also be matched with jobs where absenteeism is permitted

**Human capital** Even with the detailed data we have on degrees obtained, we find almost no impact of schooling on absenteeism except for the category “University certificate above bachelor degree”. The only two measures of human capital that are related to absenteeism decisions are seniority (positive but at a diminishing rate) and whether the individual received training in the past year (negative).

**Preference and job satisfaction** We find very strong evidence that dissatisfaction with job contracts is related to absence. Workers who indicated that they would prefer to work more hours for more pay are less often absent and workers who would prefer to work less hours for less pay are more often absent. We think this is the strongest evidence yet that absenteeism decisions act as a mechanism to adjust hours to the worker’s optimal schedule. Job satisfaction is also strongly related to absence. Workers who reported being very satisfied or satisfied with their job have 0.83 times the absence rate of dissatisfied individuals.

**Income, wage and hours** We find that, as predicted by our theoretical model, increasing income from other sources is related to more absence. The coefficient on wages is negative as predicted although the effect is not significant. We get a negative sign for contracted hours but the effect is very small. This could be due to the fact that a fair share of our sample does not work regular hours every week. Since we do not observe the contract, our measure

of contracted hours is more a measure of the number of usual hours worked on average per week.

**Work arrangement and technology use** It has been said that new work arrangements lead to more stress and more absenteeism. Using detailed data about the scheduling of the work week, we find that workers who are able to do part of their work at home are less often absent and that workers who work on a reduced workweek are more often absent. Turning to technology, we find that workers using other technologies (such as cash registers, sales terminals, scanners, etc) have a higher incidence rate of absenteeism.

**Organizational change** Firms would normally be interested in finding what organizational practices succeed in reducing absenteeism when it is costly. We find that centralization and the introduction of flexible working hours in the firm are associated with higher absenteeism, while job rotation (or multi-skilling) and outsourcing are related to lower absenteeism<sup>16</sup>. It is interesting to contrast the impact of these organizational changes in the ZIP model. For example, the impact of outsourcing shows up only in the Poisson part of the ZIP model while the impact of centralization shows up only in the inflated part. This means that outsourcing is associated with reduced incidence of absenteeism while centralization is probably associated with reduction in “permitted” absenteeism in the job design.

**Workplace practices** We find no impact for flexible job design, suggestion programs, information sharing, the use of solving teams, labour-management committees and self-directed workgroups on absenteeism<sup>17</sup>. We do however find

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<sup>16</sup>In separate work, we look at correlations between individual workplace practices in order to verify if some practices were most likely to be used in conjunction with others. Since no correlation is above 0.5, we decide against using “bundles” of practices.

<sup>17</sup>Drago and Wooden (1992) find that workgroup cohesion is associated with lower levels of absence if job satisfaction is high and Wilson and Peel (1991) find that firms with participation



that workplaces that offer family support have more absences, but this effect works through the inflated part of the Poisson model which suggests it is also due to job design.

**Cost of absenteeism** We construct two measures of the indirect cost of absenteeism. We make the hypothesis that the worker is less likely to be penalized for his absence (through lower promotion probabilities) if vacancy rates are high and layoff rates are low. Although we find that our coefficients have the expected effects, neither are statistically significant.

**Firm size, occupations, industry and time effects** We find absenteeism to be greater in large firms and for all occupations compared to managers. Interestingly, we find no interindustry differentials in the incidence of absenteeism but the large majority of industry dummies<sup>18</sup> are statistically significant in the inflated part of the ZIP model which suggests big industry differences in job design. Finally, all year dummies are negative. Since the reference year is 1999, we conclude that increases in absenteeism in that time period were probably due to changes in the workforce composition and job mix.

## 6 Conclusion

In this paper, we provide a careful examination of the factors associated with the absenteeism decision at the worker level using survey data where the information on the worker is linked to information about the workplace, something that has rarely been done. The data we use allow us to control for detailed demographic worker, job and firm characteristics. We find strong evidence that dissatisfaction with contracted hours is related to absence. We find that most schemes had significantly lower average absenteeism. These findings are not corroborated by our data.

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<sup>18</sup>The omitted category is natural resources.

human capital effects work through seniority and training. The predictions of our theoretical model are consistent with our results except for the coefficient on contracted hours which may be due to measurement error. We do not find strong indications that non traditional work arrangement lead to absenteeism. But the possibility of working at home is associated with lower absences. We find that firms that showed increased reliance on external suppliers (outsourcing) also saw absenteeism diminish.

Future work should be on devising estimation methods that would take into account the linked nature of the data. Such an estimation framework could be based on Monte Carlo Markov Chain methods to take into account the fact that the firm and worker effects are not nested. Also, it would be interesting to see if the determinants of absenteeism differ depending on the type of absenteeism (paid/unpaid, sick leave/other leave).

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## A Comparative Statics of $t^a$

### Decision with Respect to Different Parameters

The first order condition with respect to  $t^a$  is equal to:

$$E[U_L - (w(1 - s_L) + w^a)U_C] = 0.$$

We write  $H < 0$  for the second order condition that is easily verified under risk aversion. We assume that leisure is not an inferior good.

So differentiating with respect to  $R$  yields:

$$\frac{dt^a}{dR} = -\frac{1}{H}E(U_{LC} - w^t U_{CC}) > 0$$

when  $L$  is not an inferior good under certainty.

Now differentiating with respect to  $w$  yields:

$$\frac{dt^a}{dw} = \frac{1}{H}EU_C(1 - s_L) - \frac{1}{H}E(U_{LC} - w^t U_{CC})(t^c - (1 - s_L)t^a)$$

where

$$w^t \equiv w(1 - s_L) + w^a > 0.$$

This can be rewritten as

$$\frac{dt^a}{dw} = -\frac{1}{H}E[-(1 - s_L)U_C + (U_{LC} - w^t U_{CC})(t^c - (1 - s_L)t^a)]$$

which is negative under normal conditions of positive labor supply curve and when  $s_L = 0$  or small. When  $s_L = 1$ , the effect is positive.

The sign of  $dt^a/dt^c$  is given by the sign

$$\frac{dt^a}{dt^c} = -\frac{1}{H}E[U_{LC} - w^t U_{CC}]w > 0.$$

The sign of  $dt^a/dE(w^a)$  is the same as that of  $dt^a/dw^a$  under certainty.

$$\frac{dt^a}{dE(w^a)} = -\frac{1}{H}E[-U_C - (U_{LC} - w^t U_{CC})t^a] < 0$$

when  $L$  is not an inferior good under certainty.

Finally, the sign of  $dt^a/d(Risk)$  is that of

$$\frac{dt^a}{d(Risk)} \frac{1}{t^a} = U_{CC}(1 - t^a I) + U_C t^a \frac{\partial I}{\partial w^a} < 0$$

where

$$I \equiv \frac{U_{LC} - w^t U_{CC}}{U_C} > 0$$

if leisure is not an inferior good:  $1 - t^a I$  is positive when the supply curve of labor is positive and  $\partial I/\partial w^a$  is non-increasing using an intuitive condition on the variation of proportional risk aversion along the budget line (see Dionne and Eeckhoudt (1987), for more details).

## B Tables

Table 1: Summary statistics on absenteeism in Canada (1999)

	Weeks absent	
	Freq.	%
0	9,717,342	90.16
1	669,090	6.21
2	185,702	1.72
3	25,927	0.24
4	31,343	0.29
5	7,437	0.07
6	22,676	0.21
7	14,159	0.13
8	15,538	0.14
9	10,675	0.10
10	3,986	0.04
	(...)	(...)
Total	10,777,543	100.00

Table 2: Summary statistics - Employees

	1999		2001	
	Mean	Std.Dev.	Mean	Std.Dev.
<i>Dependent variable</i>				
Days of absence	5.837	19.003	5.955	9.917
<i>Demographic characteristics</i>				
Women	0.521	0.500	0.506	0.500
Black	0.011	0.104	0.014	0.119
Other race	0.280	0.449	0.309	0.462
Language	0.092	0.289	0.110	0.313
Immigrant	0.175	0.380	0.199	0.400
Years since immigration	3.988	10.181	4.361	10.594
Married	0.566	0.496	0.541	0.498
Number of pre-school aged kids	0.247	0.569	0.248	0.581
<i>Health</i>				
No activity limitation	0.955	0.208	0.937	0.243



Table 2: Cont'd

	1999		2001	
	Mean	Std.Dev.	Mean	Std.Dev.
<i>Human Capital</i>	0.107	0.309	0.120	0.325
High school degree	0.175	0.380	0.179	0.384
Industry certified training	0.020	0.141	0.011	0.104
Other training	0.033	0.179	0.022	0.147
Trade or vocational certificate	0.088	0.283	0.098	0.297
Some college	0.104	0.305	0.108	0.310
Complete college	0.181	0.385	0.188	0.391
Some university	0.077	0.266	0.067	0.249
Teacher's college	0.002	0.049	0.001	0.030
University certificate below bachelor degree	0.018	0.132	0.020	0.138
Bachelor degree	0.130	0.337	0.133	0.339
University certificate above bachelor degree	0.019	0.135	0.015	0.120
Master's degree	0.031	0.174	0.028	0.165
Degree in medicine or law	0.008	0.092	0.007	0.085
Earned doctorate	0.006	0.078	0.005	0.067
Seniority	8.745	8.192	8.518	8.206
Experience	16.167	10.714	16.411	10.993
Received training in the past year	0.369	0.483	0.339	0.473

Table 2: Cont'd

	1999		2001	
	Mean	Std.Dev.	Mean	Std.Dev.
<i>Preferences and Job Satisfaction</i>				
Would prefer to work more hours for more pay	0.191	0.393	0.217	0.412
Would prefer to work less hours for less pay	0.097	0.296	0.069	0.253
Satisfied with job	0.893	0.309	0.898	0.302
<i>Income</i>				
Total family income	65901.390	54371.310	65353.690	43994.350
Income from other sources	2325.539	11835.740	2609.757	12282.100
<i>Wage Contract</i>				
Natural logarithm of hourly wage	2.778	0.521	2.820	0.530
Contracted hours	36.623	9.837	36.237	9.711
<i>Work arrangement</i>				
Works regular hours	0.141	0.348	0.137	0.344
Usual workweek includes Saturday and Sunday	0.185	0.388	0.225	0.417
Work flexible hours	0.396	0.489	0.352	0.477
Does not work from Monday to Friday between 6am and 6pm	0.647	0.478	0.584	0.493
Some work done at home	0.267	0.443	0.231	0.422
Work some rotating shift	0.048	0.214	0.070	0.256
Work on a reduced workweek	0.049	0.215	0.079	0.269
Work on compressed work week schedule	0.031	0.173	0.055	0.228
Covered by a collective bargaining agreement	0.279	0.449	0.280	0.449
Work part time	0.051	0.220	0.053	0.224
<i>Technology</i>				
Use computer	0.608	0.488	0.601	0.490
Use computer assisted design	0.120	0.325	0.133	0.340
Use other technology	0.269	0.443	0.228	0.420
<i>Workplace Practices</i>				
FamilySupport	0.313	0.464	0.338	0.473
Nonwage	0.678	0.467	0.712	0.453

Table 2: Cont'd

	1999		2001	
	Mean	Std.Dev.	Mean	Std.Dev.
<i>Workplace Benefits</i>				
medic	0.544	0.498	0.518	0.500
life	0.579	0.494	0.572	0.495
dental	0.532	0.499	0.553	0.497
uispl	0.330	0.470	0.312	0.463
stock	0.079	0.270	0.068	0.252
empstck	0.063	0.244	0.058	0.235
<i>Professions</i>				
manager	0.151	0.358	0.112	0.315
prof	0.162	0.368	0.175	0.380
tech	0.390	0.488	0.414	0.493
sale	0.084	0.277	0.085	0.279
office	0.140	0.347	0.137	0.344
othoccup	0.074	0.262	0.077	0.267
Number of observations	23540		20377	

Table 3: Summary statistics - Employers

	1999	
	Mean	Std.Dev.
<i>Changes in organisational practices</i>		
Integration	0.247	0.431
Centralization	0.127	0.333
Downsizing	0.131	0.338
Decentralization	0.075	0.264
Temporary	0.064	0.245
Use part-time	0.126	0.332
Re-engineering	0.335	0.472
Use overtime	0.133	0.340
Adopted flexible time	0.201	0.401
Destratification	0.069	0.254
Rotation	0.253	0.435
TQM	0.205	0.404
Outsourcing	0.158	0.364
Collaboration	0.186	0.389
Other changes	0.009	0.095
<i>Workplace Practices</i>		
Suggestion program	0.303	0.460
Flexible job hours	0.308	0.462
Information sharing	0.496	0.500
Teams	0.256	0.437
Committee	0.197	0.398
Workgroups	0.103	0.305
<i>Cost of absenteeism</i>		
Vacancy rate	0.026	0.062
Layoff rate	0.101	0.374

Table 3: Cont'd

	1999	
	Mean	Std.Dev.
<i>Size</i>		
10-19 employees	0.461	0.499
20-99 employees	0.460	0.498
100-499 employees	0.070	0.255
500 employees and more	0.010	0.098
<i>Industry</i>		
Natural resources	0.015	0.120
Primary product manufacturing	0.025	0.156
Secondary product manufacturing	0.030	0.170
Labour intensive tertiary manufacturing	0.045	0.208
Capital intensive tertiary manufacturing	0.048	0.214
Construction	0.053	0.223
Transportation	0.134	0.340
Communication and other utilities	0.022	0.146
Retail trade and consumer service	0.302	0.459
Finance and insurance	0.069	0.253
Real estate	0.014	0.117
Business services	0.110	0.313
Education and health services	0.103	0.304
Information and cultural industries	0.031	0.174

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N = 4072

Table 4: Poisson regressions on days of absenteeism

	Poisson Model		RE ZIP Poisson	
	Coef.	IRR	Poisson	Inflate
<i>Demographic characteristics</i>				
Women	0.161** (0.065)	1.174** (0.076)	0.075 (0.060)	-0.244*** (0.064)
Black	-0.100 (0.152)	0.905 (0.138)	-0.061 (0.135)	0.070 (0.168)
Other race	-0.051 (0.060)	0.950 (0.057)	-0.001 (0.056)	0.146*** (0.057)
Language at work differs from the one at home	0.045 (0.067)	1.046 (0.070)	0.011 (0.063)	-0.095 (0.079)
Immigrant	-0.134 (0.141)	0.875 (0.124)	-0.095 (0.130)	0.109 (0.127)
Years since immigration	0.004 (0.006)	1.004 (0.006)	0.004 (0.005)	0.000 (0.005)
Married	-0.092* (0.049)	0.912* (0.044)	-0.067 (0.047)	0.087* (0.051)
Number of pre-school aged kids	-0.160*** (0.057)	0.852*** (0.048)	-0.127*** (0.046)	0.089 (0.067)
Women * pre-school aged kids	0.248*** (0.078)	1.282*** (0.100)	0.221*** (0.070)	-0.108 (0.093)
<i>Health</i>				
No activity limitation	-0.857*** (0.067)	0.424*** (0.029)	-0.711*** (0.064)	0.460*** (0.080)

Statistical significance: \*=10%; \*\*=5%; \*\*\*=1%.

Robust standard error in parantheses

Table 4: Cont'd

	RE Poisson		RE ZIP Poisson	
	Coef.	IRR	Poisson	Inflate
<i>Human Capital</i>				
High school degree	-0.115 (0.098)	0.892 (0.087)	-0.153* (0.091)	-0.043 (0.082)
Industry certified training	0.011 (0.167)	1.011 (0.169)	-0.089 (0.149)	-0.138 (0.216)
Other training	-0.086 (0.177)	0.918 (0.162)	-0.202 (0.165)	-0.162 (0.132)
Trade or vocational certificate	0.096 (0.110)	1.101 (0.122)	0.040 (0.100)	-0.168 (0.101)
Some college	0.156 (0.112)	1.169 (0.130)	0.054 (0.103)	-0.249** (0.102)
Complete college	-0.028 (0.109)	0.972 (0.106)	-0.103 (0.102)	-0.198** (0.089)
Some university	0.064 (0.121)	1.066 (0.129)	-0.012 (0.113)	-0.183* (0.107)
Teacher's college	-0.189 (0.275)	0.828 (0.228)	-0.412** (0.173)	-0.675 (0.432)
University certificate below bachelor degree	-0.005 (0.148)	0.995 (0.147)	-0.078 (0.136)	-0.142 (0.136)
Bachelor degree	-0.029 (0.119)	0.971 (0.115)	-0.105 (0.111)	-0.164 (0.118)
University certificate above bachelor degree	0.469** (0.186)	1.598** (0.298)	0.378** (0.173)	-0.152 (0.159)
Master's degree	0.025 (0.158)	1.026 (0.162)	-0.059 (0.152)	-0.153 (0.181)
Degree in medicine or law	-0.340* (0.205)	0.712* (0.146)	-0.344* (0.181)	0.088 (0.285)
Earned doctorate	0.238 (0.461)	1.269 (0.586)	0.324 (0.464)	0.190 (0.324)
Seniority	0.037*** (0.009)	1.037*** (0.009)	0.033*** (0.009)	-0.010 (0.010)
Seniority squared (/100)	-0.101*** (0.028)	0.904*** (0.025)	-0.084*** (0.027)	0.039 (0.029)
Experience	-0.013 (0.008)	0.987 (0.008)	-0.011 (0.008)	0.008 (0.008)
Experience squared (/100)	0.021 (0.018)	1.021 (0.019)	0.022 (0.017)	0.000 (0.017)
Received training in the past year	-0.115** (0.051)	0.892** (0.045)	-0.185*** (0.047)	-0.209*** (0.052)

Statistical significance: \*=10%; \*\*=5%; \*\*\*=1%.

Robust standard error in parantheses

Table 4: Cont'd

	RE Poisson		RE ZIP Poisson	
	Coef.	IRR	Poisson	Inflate
<i>Preferences and Job Satisfaction</i>				
Would prefer to work more hours for more pay	-0.119*	0.888*	-0.151**	-0.053
	(0.069)	(0.061)	(0.065)	(0.058)
Would prefer to work less hours for less pay	0.258***	1.294***	0.160**	-0.265***
	(0.066)	(0.085)	(0.064)	(0.079)
Satisfied with job	-0.192***	0.825***	-0.130*	0.154***
	(0.072)	(0.059)	(0.067)	(0.067)
<i>Income</i>				
Total family income (000s)	-0.000	1.000	-0.000	0.000
	(0.001)	(0.001)	(0.001)	(0.001)
Income from other sources (000s)	0.002***	1.002***	0.002***	-0.003
	(0.001)	(0.001)	(0.001)	(0.002)
<i>Wage Contract</i>				
Natural logarithm of hourly wage	-0.103	0.902	-0.086	0.110
	(0.074)	(0.066)	(0.070)	(0.074)
Contracted hours	-0.005	0.995	-0.010**	-0.006
	(0.004)	(0.004)	(0.005)	(0.003)
<i>Work arrangement</i>				
Works regular hours	0.052	1.053	0.195**	0.335***
	(0.086)	(0.091)	(0.078)	(0.068)
Usual workweek includes Saturday and Sunday	-0.028	0.972	0.015	0.099
	(0.081)	(0.078)	(0.076)	(0.080)
Work flexible hours	0.010	1.010	0.035	0.074
	(0.053)	(0.053)	(0.050)	(0.047)
Does not work from MtoF between 6am and 6pm	-0.037	0.964	-0.086	-0.221***
	(0.072)	(0.070)	(0.068)	(0.066)
Some work done at home	-0.122*	0.885*	-0.070	0.126*
	(0.074)	(0.065)	(0.071)	(0.065)
Work some rotating shift	0.021	1.022	-0.034	-0.138
	(0.096)	(0.098)	(0.091)	(0.085)
Work on a reduced workweek	0.270**	1.310**	0.252**	-0.059
	(0.107)	(0.141)	(0.101)	(0.100)
Work on compressed work week schedule	0.012	1.012	0.044	0.034
	(0.093)	(0.094)	(0.085)	(0.091)
Covered by a collective bargaining agreement	0.278***	1.320***	0.193***	-0.238***
	(0.058)	(0.076)	(0.056)	(0.057)
<i>Technology</i>				
Use computer	-0.081	0.922	-0.112	-0.054
	(0.075)	(0.069)	(0.069)	(0.058)
Use computer assisted design	0.084	1.088	0.054	-0.108**
	(0.061)	(0.066)	(0.059)	(0.056)
Use other technology	0.134***	1.143***	0.075	-0.157***
	(0.052)	(0.059)	(0.049)	(0.054)

Statistical significance: \*=10%; \*\*=5%; \*\*\*=1%.

Robust standard error in parantheses<sup>31</sup>



Table 4: Cont'd

	RE Poisson		RE ZIP Poisson	
	Coef.	IRR	Poisson	Inflate
<i>Changes in organisational practices</i>				
Integration	-0.064 (0.055)	0.938 (0.052)	-0.066 (0.052)	-0.041 (0.063)
Centralization	0.121* (0.062)	1.128* (0.070)	0.068 (0.059)	-0.182*** (0.057)
Downsizing	-0.018 (0.050)	0.982 (0.050)	-0.009 (0.048)	0.020 (0.052)
Decentralization	0.007 (0.076)	1.007 (0.076)	0.009 (0.072)	0.013 (0.079)
Temporary	0.007 (0.065)	1.007 (0.065)	-0.022 (0.063)	-0.147** (0.069)
Use part-time	0.011 (0.066)	1.011 (0.067)	0.017 (0.064)	0.049 (0.066)
Re-engineering	0.039 (0.060)	1.040 (0.062)	0.058 (0.057)	0.075 (0.057)
Use overtime	-0.059 (0.060)	0.943 (0.057)	-0.050 (0.058)	0.081 (0.069)
Adopted flexible time	0.185*** (0.063)	1.203*** (0.075)	0.173*** (0.059)	-0.069 (0.061)
Destratification	0.094 (0.063)	1.098 (0.069)	0.093 (0.060)	0.052 (0.065)
Rotation	-0.171*** (0.053)	0.843*** (0.045)	-0.093* (0.051)	0.164*** (0.057)
TQM	0.000 (0.052)	1.000 (0.052)	-0.038 (0.050)	-0.103* (0.055)
Outsourcing	-0.120** (0.056)	0.887** (0.050)	-0.112** (0.053)	0.009 (0.064)
Collaboration	-0.024 (0.056)	0.976 (0.054)	-0.046 (0.053)	-0.021 (0.057)
Other changes	0.029 (0.186)	1.029 (0.191)	0.064 (0.175)	0.112 (0.108)

Statistical significance: \*=10%; \*\*=5%; \*\*\*=1%.

Robust standard error in parantheses

Table 4: Cont'd

	RE Poisson		RE ZIP Poisson	
	Coef.	IRR	Poisson	Inflate
<i>Workplace Practices</i>				
Suggestion program	0.058 (0.054)	1.060 (0.057)	0.080 (0.050)	0.009 (0.058)
Flexible working hours	-0.055 (0.060)	0.946 (0.057)	-0.047 (0.055)	0.070 (0.056)
Information sharing	-0.014 (0.058)	0.986 (0.057)	-0.045 (0.054)	-0.053 (0.059)
Problem solving teams	-0.007 (0.060)	0.993 (0.059)	-0.005 (0.055)	-0.023 (0.054)
Labour management committee	0.016 (0.065)	1.017 (0.066)	-0.004 (0.061)	-0.066 (0.054)
Self-directed workgroups	-0.091 (0.070)	0.913 (0.064)	-0.076 (0.064)	0.039 (0.060)
Family support	0.109** (0.049)	1.115** (0.055)	0.066 (0.047)	-0.175*** (0.048)
Non wage benefits	-0.044 (0.100)	0.957 (0.096)	-0.138 (0.091)	-0.151 (0.093)
Participate in supp. medical insurance	0.132** (0.067)	1.141** (0.076)	0.125** (0.063)	0.012 (0.061)
Participate in supp. life/disability insurance	0.148* (0.077)	1.159* (0.090)	0.071 (0.070)	-0.212*** (0.068)
Participate in a dental plan	-0.063 (0.080)	0.939 (0.075)	-0.074 (0.074)	-0.107 (0.073)
Emp. offers supp. to EI ben. for parental leave	0.025 (0.051)	1.026 (0.052)	0.048 (0.047)	0.092* (0.048)
Participate in a stock purchase plan	0.247 (0.195)	1.281 (0.250)	0.276 (0.176)	0.166 (0.152)
Employer contributes to stock purchase plan	-0.167 (0.219)	0.846 (0.186)	-0.164 (0.197)	-0.143 (0.161)
<i>Cost of absenteeism</i>				
Vacancy rate	0.359 (0.591)	1.432 (0.847)	0.461 (0.572)	0.327 (0.523)
Layoff rate	-0.011 (0.062)	0.989 (0.061)	0.013 (0.042)	0.031 (0.047)

Statistical significance: \*=10%; \*\*=5%; \*\*\*=1%.

Robust standard error in parantheses

Table 4: Cont'd

	RE Poisson		RE ZIP Poisson	
	Coef.	IRR	Poisson	Inflate
<i>Firm Size</i>				
20-99 employees	0.142*	1.152*	0.131*	0.013
	(0.080)	(0.093)	(0.073)	(0.094)
100-499 employees	0.276***	1.317**	0.240***	-0.076
	(0.088)	(0.115)	(0.081)	(0.097)
500 employees and more	0.171*	1.187*	0.163*	-0.034
	(0.094)	(0.111)	(0.086)	(0.109)
<i>Occupation</i>				
Professional	0.212**	1.237**	0.128	-0.178*
	(0.102)	(0.126)	(0.092)	(0.100)
Technician/Trades	0.270***	1.310***	0.187**	-0.130
	(0.103)	(0.135)	(0.093)	(0.088)
Sales/Marketing	0.127	1.135	-0.016	-0.183
	(0.144)	(0.164)	(0.132)	(0.143)
Clerical/Administrative	0.157	1.170	0.032	-0.279***
	(0.114)	(0.133)	(0.102)	(0.101)
Other	0.297*	1.346*	0.233*	-0.065
	(0.153)	(0.206)	(0.140)	(0.121)

Statistical significance: \*=10%; \*\*=5%; \*\*\*=1%.

Robust standard error in parantheses

Table 4: Cont'd

	RE Poisson		RE ZIP Poisson	
	Coef.	IRR	Poisson	Inflate
<i>Industry</i>				
Primary product manuf.	-0.006 (0.163)	0.994 (0.162)	-0.097 (0.153)	-0.181* (0.106)
Secondary product manuf.	-0.059 (0.172)	0.943 (0.162)	-0.210 (0.163)	-0.280*** (0.110)
Labour intensive tertiary manufac.	-0.119 (0.159)	0.888 (0.141)	-0.255* (0.147)	-0.294*** (0.114)
Capital intensive tertiary manufac.	-0.101 (0.158)	0.904 (0.143)	-0.233 (0.146)	-0.265** (0.108)
Construction	0.117 (0.178)	1.125 (0.200)	0.072 (0.165)	-0.057 (0.134)
Transportation	-0.060 (0.158)	0.942 (0.149)	-0.180 (0.147)	-0.273*** (0.110)
Communication and other utilities	0.086 (0.176)	1.089 (0.192)	-0.123 (0.166)	-0.486*** (0.120)
Retail trade	-0.035 (0.162)	0.966 (0.156)	-0.194 (0.151)	-0.343*** (0.120)
Finance and insurance	0.093 (0.161)	1.098 (0.177)	-0.184 (0.148)	-0.691*** (0.135)
Real estate	-0.311* (0.178)	0.733* (0.130)	-0.538*** (0.159)	-0.507** (0.215)
Business services	-0.008 (0.160)	0.992 (0.159)	-0.245* (0.148)	-0.541*** (0.117)
Education and health services	0.228 (0.156)	1.257 (0.196)	-0.045 (0.144)	-0.673*** (0.113)
Information and cultural industries	-0.021 (0.189)	0.979 (0.185)	-0.272 (0.180)	-0.550*** (0.125)
<i>Year Dummies</i>				
Year = 2000	0.011 (0.065)	1.011 (0.066)	-0.104* (0.061)	-0.340*** (0.049)
Year = 2001	-0.057 (0.066)	0.944 (0.062)	-0.168*** (0.061)	-0.339*** (0.060)
Year = 2002	-0.101 (0.068)	0.904 (0.062)	-0.211*** (0.064)	-0.305*** (0.064)
Constant	2.557*** (0.406)		3.696*** (0.388)	0.522* (0.285)
Observations	63539			

Statistical significance: \*=10%; \*\*=5%; \*\*\*=1%.

Robust standard error in parantheses